

Stat 564
11-16-17

A different way to interpret
the slope estimator in simple
linear regression

①

$$\sum_{i=1}^{n-1} \sum_{j=i+1}^n (y_j - y_i)(x_j - x_i)$$
$$= \underline{\sum \sum y_j x_j} - \underline{\sum \sum y_i x_i} - \underline{\sum \sum y_i x_j} + \underline{\sum \sum y_j x_i}$$

Positive terms (single underline)

②

$$\sum_{i=1}^{n-1} \sum_{j=i+1}^n y_j x_j + \sum_{i=1}^{n-1} \sum_{j=i+1}^n y_i x_i$$
$$= \sum_{j=2}^n \sum_{i=1}^{j-1} y_j x_j + \sum_{i=1}^{n-1} (n-i) y_i x_i$$
$$= \sum_{j=2}^n (j-1) y_j x_j + \sum_{i=1}^{n-1} (n-i) y_i x_i$$
$$= \sum_{i=2}^n (i-1) y_i x_i + \sum_{i=1}^{n-1} (n-i) y_i x_i$$

$$= \sum_{i=1}^n (i-1) y_i x_i + \sum_{i=1}^n (n-i) y_i x_i$$

(3)

$$= \sum_{i=1}^n (n-1) y_i x_i = (n-1) \sum_{i=1}^n y_i x_i$$

Negative terms (double underline)

$$\sum_{i=1}^{n-1} \sum_{j=i+1}^n y_j x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^n y_i x_j$$

$$= \sum_{i=1}^{n-1} \left[x_i \sum_{j=i+1}^n y_j \right] + \sum_{j=2}^n \sum_{i=1}^{j-1} y_i x_j$$

(4)

$$= \sum_{i=1}^{n-1} \left[x_i \sum_{j=i+1}^n y_j \right] + \sum_{j=2}^n \left[x_j \sum_{i=1}^{j-1} y_i \right]$$

$$= x_1 \sum_{j=2}^n y_j + \sum_{i=2}^{n-1} \left[x_i \sum_{j=i+1}^n y_j \right]$$

$$+ x_n \sum_{i=1}^{n-1} y_i + \sum_{j=2}^{n-1} \left[x_j \sum_{i=1}^{j-1} y_i \right]$$

$$\begin{aligned}
 &= x_1 \left[\sum_{j=1}^n y_j - y_1 \right] + x_n \left[\sum_{i=1}^n y_i - y_n \right] \quad (5) \\
 &\quad + \underbrace{\sum_{i=2}^{n-1} \left[x_i \sum_{j=i+1}^n y_j \right] + \sum_{i=2}^{n-1} \left[x_i \sum_{j=1}^{i-1} y_j \right]} \\
 &\quad \sum_{i=2}^{n-1} \left[x_i \left(\sum_{j=1}^n y_j - y_i \right) \right]
 \end{aligned}$$

$$= \sum_{i=1}^n x_i \left(\sum_{j=1}^n y_j - y_i \right)$$

$$\begin{aligned}
 &= \sum_{i=1}^n x_i (n\bar{y} - y_i) = n\bar{y} \underbrace{\sum_{i=1}^n x_i}_{n\bar{x}} - \sum_{i=1}^n x_i y_i \quad (6) \\
 &= n^2 \bar{x} \bar{y} - \sum_{i=1}^n x_i y_i
 \end{aligned}$$

Reassemble the original double summation:

$$\begin{aligned}
 &(n-1) \sum_{i=1}^n x_i y_i - \left[n^2 \bar{x} \bar{y} - \sum_{i=1}^n x_i y_i \right] \\
 &= n \sum_{i=1}^n x_i y_i - n^2 \bar{x} \bar{y} = n \left[\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y} \right]
 \end{aligned}$$

$$= n S_{xy}$$

(7)

$$\therefore n S_{xy} = \sum_{i=1}^{n-1} \sum_{j=i+1}^n (y_j - y_i)(x_j - x_i)$$

$$\text{Similarly, } n S_{xx} = \sum_{i=1}^{n-1} \sum_{j=i+1}^n (x_j - x_i)^2$$

$$\text{Recall } \hat{\beta}_1 = \frac{S_{xy}}{S_{xx}} = \frac{\sum \sum (y_j - y_i)(x_j - x_i)}{\sum \sum (x_j - x_i)^2}$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^n (x_j - x_i)^2 \frac{y_j - y_i}{x_j - x_i}}{\sum_{i=1}^{n-1} \sum_{j=i+1}^n (x_j - x_i)^2}$$

(8)

Note: our least squares slope estimator is, in fact, a weighted average of every possible pairwise slope, where the weights are $(x_j - x_i)^2$

P.K. Sen (1968) proposed

(9)

using the median of all pairwise slopes
to estimate β_1

This is now called the Theil-Sen estimator

$$\begin{aligned}\text{Recall } \hat{\beta}_0 &= \bar{y} - \hat{\beta}_1 \bar{x} \\ &= \frac{1}{n} \sum_{i=1}^n (y_i - \hat{\beta}_1 x_i)\end{aligned}$$

The Theil-Sen estimator of the
intercept is the median of
the $y_i - \hat{\gamma}_1 x_i$ terms, where

$\hat{\gamma}_1$ was the Theil-Sen slope estimator

(10)

No new
HW